Mobility, Education and Labor Market Outcomes for U.S. Graduates: Is Selectivity Important? *

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Accepted at *The Annals of Regional Science*

ABSTRACT

The literature on human capital, and its positive effects on individuals and regional economies, is now vast. The linkages between human capital and migration have also found a fertile ground in recent years especially in Europe where many studies have focused on interregional migration of graduates and highly skilled individuals. However, the literature on this phenomenon in the USA is less developed. Using the SESTAT database from NSF, this paper aims at contributing to the understanding of inter-state migration behavior of graduates in the USA and its effects on their career outcomes. It builds on the existing literature not only by focusing specifically on the US context, but also incorporating into the empirical model a correction for the possible selection bias that arises from the dual relationship between migration propensity and human capital endowment. Our estimated Mincerian earning equations, corrected for migrant self-selectivity, show that indeed repeat migration is associated with higher average salaries, while late migration is associated with a salary penalty. As for the other control variables, our results are consistent with what has been found in the labor economics literature. Female workers suffer from a salary penalty, while experience, level of education and employer size are all associated with higher average salaries. The labor market also rewards different fields of study differently.

JEL classification: I23, J21, J24, J31, J61, R23

Keywords: Selection-bias correction, Domestic Migration, Wage differentials, Human capital, Returns to education

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* We are indebted to the National Science Foundation and specifically the National Center for Science and Engineering Statistics for providing the SESTAT data. They bear no responsibility for the analysis conducted or interpretation of the data. All remaining errors are ours.

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1. INTRODUCTION

Since the pioneering work by Mincer (1958), Schultz (1961) and Becker (1962) the concept of human capital has become central to economics. Human capital is beneficial not only to individuals but to society overall. Romer (1986) and Lucas (1988), proved that human capital is one of the driving forces of economic development and that it generates positive externalities which go above and beyond individual benefits.

Although many researchers focused on the direct impact of human capital, measured by formal education, on wages and growth, less is known about the relationship between migration and human capital and the role of migration—especially for educational purposes—plays in future career paths after graduation. Migration itself can be seen as a form of investing in human capital. By migrating, people acquire knowledge and experience, which increase their stock of human capital (Faggian, 2005). It is also interesting to note that education appears to significantly increase an individual's tendency to migrate (Faggian et al., 2007), suggesting that migration and education may be complementary rather than substitute forms of investing in human capital.

This complementarity becomes clear when looking at high school leavers and college graduates. The period immediately before or after a lengthy investment in human capital is when migration propensity is at its peak. High school leavers use migration as a way to select the best higher education institution, hence maximizing their investment in human capital. College graduates use migration to find the best job matching their acquired human capital, hence maximizing its returns.

While several contributions from Europe (Faggian and McCann 2009 and Faggian et al. 2007a, b, 2013 for the UK; Venhorst et al. 2010, 2011 for the Netherlands; Iammarino and Marinelli 2011, 2015, Marinelli 2012, and Dotti et al. 2012 for Italy; Haapanen and Tervo 2006 for Finland) and more recently Australia (Corcoran et al. 2010) focused on student and graduate mobility, the contributions from the USA are still rather limited. Franklin (2003) shows that, in the case of the United States in the period covered by the 2000 Census, younger individuals (aged 25–39) with a college degree were much more mobile than their peers without a degree. This analysis, though, was at the aggregate—not individual—level and focused on macro-level patterns of movement rather than individual determinants and consequences.

This paper, using the SESTAT database by the National Science Foundation (NSF), aims at filling this gap in the US literature by studying the inter-state migration behavior of college graduates and its effects on their career. It builds on the existing literature not only by focusing specifically on the US context, but also incorporating into the empirical model a correction for the possible selection bias that arises from the (dual) relationship between migration propensity and the initial level of human capital.

By estimating Mincerian earning equations, augmented with migration variables, we find that indeed more migratory graduates have higher average salaries even after controlling for endogenous selection. As for the other control variables, our results are consistent with what has been found in the labor economics literature. Female workers suffer from a salary penalty, while experience, level of education and employer size are all associated with higher average salaries. The labor market also rewards different fields of study differently.

The paper is organized as follows. Section 2 presents a brief literature review of the topic, followed by the empirical framework in Section 3. Section 4 describes the data and variables used in the analysis. Section 5 discusses the main results and finally Section 6 offers some concluding remarks and possible ways forward.

2. THEORETICAL BACKGROUND

Sjaastad (1962) was the first to acknowledge that migration can be considered an investment activity, which has costs and renders returns. Individuals who migrate are supposed to do so because they expect the returns from migration to outweigh the costs, at least in the long run.

Following Hart (1975), this can be formalized by equation (1). Assuming a potential migrant wants to move from region i to region j, the movement will occur only if the expected value of utility derived from the net present value of their expected returns (R_i) in the origin region i (origin) is less than that in the destination region j minus the costs associated with relocation (C_{ij}):

$$E\{U[R_i](0)\} < E\{U[R_j](0)\} - E\{C_{ij}(0)\} \qquad (1)$$

where the zero in parenthesis simply means that earnings and cost are evaluated at the present time ($t = 0$). As Sabot (1987) showed, there seems to be a positive interaction between education and migration, so that the net benefits of migrating for highly educated individuals are proportionately higher than those for less educated ones.

The reasons for such an interaction lie on both the returns and costs sides. On the returns side, migration allows educated individuals to find a better job match to fully exploit their skills (see Harmon et al., 2000; Di Cintio and Grassi, 2013; Jewell and Faggian, 2014). On the costs side, education makes individuals more capable of finding and processing information (DaVanzo, 1983), less reliant on the support network of family and friends—hence reducing their psychological moving costs (DaVanzo and Morrison, 1981)—and more adaptable to new living conditions and cultural environment (Levy and Wadycki, 1974). Moreover, there is also a considerable learning process in migrating. Young adults who migrate away from home to get an education, are more likely to move again after graduating. Faggian et al. (2007a, b) show that, in the UK, previous migration (away from the parental domicile to university location) is one of the strongest predictors for subsequent migration (from university to job location). Murphy-Lejeune (2002) uses the idea of *mobility capital* to describe how students with mobility experience develop a taste for it and, as a result, they are much more likely to work in a different location later on in life.

The complex relationship between education and migration makes it difficult to exactly disentangle the effects of migration on individual welfare (e.g. measured by labor income). The problem of self-selection is crucial. If individuals with a higher migration propensity are also the ones with higher innate abilities and skills, then returns to migration could be over-estimated in a traditional model that does not correct for this.

Roy (1951) was the first to acknowledge the problem of self-selection of individuals into different occupations according to their skills. In the late 70s, 80s the idea of self-selection became more common in the labor economics literature (Willis and Rosen, 1979;

Heckman and Sedlacek 1985). However, it was not until the Borjas' 1987 paper published in the American Economic Review that the idea was applied to (international) migration. Borjas presented a simple parametric two-sector Roy model to discuss the relationship between self-selection and the earnings of immigrants in the USA. His main insight was that people migrating from an origin country, say Mexico, to the USA are not randomly drawn from the population of that country. In deciding whether to migrate or not, each individual follows a maximization procedure comparing the net benefits at the origin and at destination. Three are the possible outcomes of the model: positive hierarchical sorting, negative hierarchical sorting and refugee sorting. Positive hierarchical sorting occurs when immigrants are (skill-wise) positively selected from the source country population distribution and hence they end up with above the mean earnings in the host country. Negative sorting is the opposite case. Refugee sorting is the special case where highly skilled individuals are discriminated in the origin country, and hence they are under-performing, but they end up with above mean earnings in the host country where they can exploit their full potential.

Few years after his contribution on international migration, Borjas (1992) also applied the Roy theoretical framework to the study of internal migration in the USA. Borjas sees the Roy model as alternative to the Hicks-Sjaastad model in that "*the Hicks-Sjaastad model emphasizes the fact that mean income levels differ across regions, and these income differentials (net of migration costs) generate unidirectional migration flows*", while the Roy model "*stresses regional differences in the returns to skills (as well as regional' differences in mean income)*" and they are ultimately these skill-price differentials that "*determine the skill composition of migration flows"* (p. 160). Using the National Longitudinal Survey of Youth (NLSY), he finds that individuals are more likely to migrate the greater is the mismatch between their skill endowments and the returns paid to skills in their native state. Moreover, skilled workers seem to benefit from locations with greater skill dispersion.

While we agree with the Borjas' point that returns to skills, as emphasized by Roy, should take central stage in the study on internal migration flows, we are not in total agreement with him in seeing the Roy model as an alternative to the more traditional human capital migration model *à la* Sjaastad (1962). In fact, the two seem more complementary than substitutable. Self-selection can be incorporated in a framework still based on the traditional human capital migration model. In this respect, our approach is similar to Abreu et al. (2015), although their paper studied the joint effect of changing location and industry on graduate salaries, while we are focusing on the effect of migration.

Not only we believe that migrants might have different characteristics than non-migrants (that might affect also their future salary), but in addition we believe that different ‘types’ of migrations should also be distinguished. Following Faggian et al. (2007a, b) we classify graduates according to their ‘sequential migration’ behavior which is the result of two separate migration choices: the first one from domicile to university and the second one, after graduation, from university to first job location. The combination of these two migration decisions gives raise to five different ‘sequential migration typologies’ (Figure 1).[1]

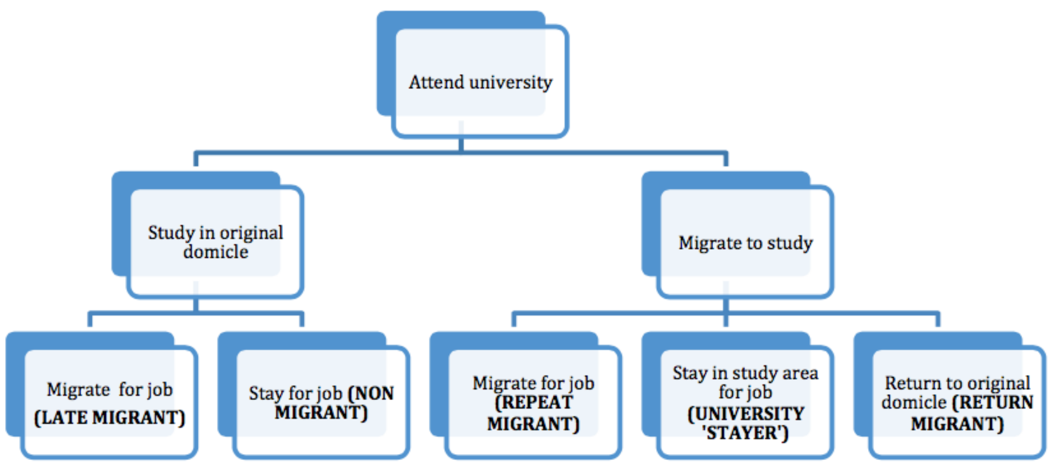

Figure 1: Sequential migration typologies. Source: Jewell and Faggian (2014)

Repeat migrants (RE) are the most migratory group changing location for both study and work purposes. Return migrants (RT) also move twice, but the second movement is to return to their original location. University ‘stayer’ (US) and late migrants

[1] Although, ideally, we would like to classify individuals defining migration at country-level, location was only available at state level, so migration is defined as a change of state. This leaves out any interstate migration consideration for which data were not available.

(LM) are complementary to each other. The former move to study but then stay in the university location to enter the labor market; the latter do not move away to study, but then move away to work. Non-migrants (NM) never moved.

The basic hypothesis to be tested in this paper is whether a higher migration propensity is associated, on average, with higher salaries. Not only, by correcting for selectivity issues, we also want to test whether the higher salaries are truly a function of the willingness to move to find a more appropriate job or whether it is simply the case that the most migratory people are also the most capable. Previous studies from the UL (Jewell and Faggian, 2014) have shown that repeat and late migrants are the most successful in the labor market. However, they did not test for the issue of migrant self-selectivity.

Generally, migration studies classify individuals into migrants and non-migrants. However, this means that they do not distinguish between, repeat, return and late migrants —who all migrate to work—on one side and university stayers and non-migrants—who do not migrate to work—on the other. Several studies, going back to DaVanzo (1983) to the more recent work by Faggian et al. (2006, 2007a, b) for the UK, show that repeat and return migrants, for instance, have different characteristics and salaries, so grouping them would conceal some interesting patterns.

3. EMPIRICAL STRATEGY

The theoretical work highlighting the importance of self-selection was pivotal for all the empirical work that followed. The Heckman selection model (Heckman, 1979) and the use of instrumental variables for consistent estimation when endogeneity is present, were a response to the realization that self-selection (and endogeneity) could potentially create serious biases in results. However, one of the limitations of the standard Heckman selection model is that it assumes a dichotomous selection process. In the first stage individuals can only belong to one of two categories, 0 (non-participation) or 1 (participation) and their probability to belong to each category is estimated via a probit model. Deb and Trivedi's (2006) "multinomial treatment effects model" extends the Heckman model to allow for a multi-categorical (polychotomous) selection effect in the first stage.

We apply the Deb and Trivedi's model to the case of migrant selection by estimating, in the first stage, each individual's choice among a set of possible mutually exclusive choices ("treatment"). In our case the choices are the five sequential migration categories (j=1,2,3,4,5): repeat migrant, return migrant, university stayer, late migrant and non-migrant. University stayer is selected as base category. The indirect utility (V) associated with the *j-th* treatment for the *i-th* individual can be expressed as:

$$V_{ij} = \boldsymbol{z}_i \alpha_j + \delta_j l_{ij} + \eta_{ij} \tag{2}$$

$\mathbf{z}_i$ is a vector of exogenous variables (with the associated parameters α_j and *i.i.d.* error terms η_{ij}). The indirect utility V_{ij} includes a vector of latent-characteristics, l_{ij}, that influence both the treatment chosen by the individual and the final outcome in the second stage (in our case salary). While the indirect utility function (and the latent variables) cannot be observed, one can infer the nature of the selection process by looking at the observed treatment, which is represented by a series of dummy variables. In our case the observed treatment is the sequential migration category picked by the individual and the set of dummy variables can be written as $\boldsymbol{d_i} = [d_{iRE}, d_{iRT}, d_{iUS}, d_{iLM}, d_{iNM}]$ with d_{iUS} as excluded dummy (base category).

The probability of choosing a sequential migration category can be modeled as a mixed multinomial logit (MML):

$$\Pr(\boldsymbol{d_i} | \boldsymbol{z}_i, l_i) = \frac{\exp(\boldsymbol{z_i'} \alpha_j + l_{ij})}{1 + \sum_{k=1}^{J} \exp(\boldsymbol{z_i'} \alpha_k + l_{ik})} \tag{3}$$

The results from the first stage MML are then incorporated in the second stage outcome equation, in our case a Mincerian earning equation with the logarithm of annual salaries as dependent variable.[2]

[2] Notice that, as Deb and Trivedi (2006) discuss, the model requires normalization restrictions on the scale of each choice and on the variance-covariance parameters. The last condition can be met

$$E(y_i) = \mu\left(\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta} + \sum_{\boldsymbol{j}=\boldsymbol{1}}^{\boldsymbol{J}} \gamma_j d_{ij} + \sum_{j=1}^{J} \lambda_j l_{ij}\right) \quad (4)$$

, where $\boldsymbol{x}_i$ is a vector of observable individual characteristics, d_{ij} are the dummy variables defining the migration choice (as before) and $\lambda_j l_{ij}$ is the correction terms from the first stage.

The model parameters can be estimated using maximum simulated likelihood (MSL). As this method needs to evaluate integrals that may not have a closed form solution, an acceleration technique using quasi-random draws based on Halton sequences is used.

4. DATA AND MODELLING

4.1 DATA

The main source of data in our study is SESTAT (Scientists and Engineers Statistical Data System) provided to us by the National Science Foundation (NSF) under a restricted license agreement. SESTAT is a combination of three surveys:

- The National Survey of College Graduates (NSCG)
- The National Survey of Recent College Graduates (NSRCG)
- The Survey of Doctorate Recipients (SDR)

The surveys have been conducted biennially since the 1970s and include data on United States residents who hold at least a bachelor's degree in science or engineering, or who worked in science or engineering occupations during the survey week. Despite the limitation on the fields, SESTAT is a unique source of information for examining various characteristics of college-educated individuals, including occupation, work

when $\delta_{jk} = 0 \; \forall \; j \neq k$. Thus, if this holds, then each choice is affected by a unique latent factor. Furthermore, in order to normalize the scale of each choice equation, you need to set $\delta_{jj} = 1 \; \forall \; j$.

activities, salary, the relationship of degree field and occupation, and demographic information. In this contribution, we focus on the 2010 survey, which was the last available year and the one with the largest sample. Once restricting to only individuals aged 25-69 and to those in full-time employment, the final number of valid observations was 14,542.[3]

The SESTAT data were then combined with other data form the U.S. Bureau of Labor Statistics, the U.S. Bureau of Census, the City and County Databook (2007), and the U.S. National Oceanic and Atmospheric Administration.

4.2 VARIABLES INCLUDED IN THE MODEL

The dependent variable in our Mincerian earning equation is the logarithm of individual salary. This information comes from the SESTAT data and is the annual pretax salary. We use the annual salary, rather than the hourly or weekly one, because there is no reliable information on the weeks/hours worked per year (due to a large number of missing values). Nevertheless, we do have information on whether an individual was employed part-time or full-time and we restricted our analysis to full-time workers only.

Although a series of control for individual, education and job characteristics are included, our variables of interest are the dummy variables describing the sequential migration behavior of individuals (*REPEAT*, *RETURN*, *LATEMIG* and *UNISTAY*, with *NONMIG* as excluded dummy). So, our final Mincer equation can be expressed as:

$$\log w_i = \alpha_i + \boldsymbol{\beta IND}_i + \boldsymbol{\gamma EDU}_i + \boldsymbol{\delta JOB}_i + \\ + \theta_1 REPEAT + \theta_2 RETURN + \theta_3 LATEMIG + \theta_4 UNISTAY + \varepsilon_i \qquad (6)$$

, where **IND**, **EDU** and **JOB** are vectors of individual, education and job-related characteristics.

[3] To check the robustness of our results, we also estimated our models for individuals aged 25-40. Results are reported in Table 6. The restriction to younger individuals does not change the results for the large majority of our regressors, and the selection and endogeneity are still important factors. However, some of the selection terms do change sign, the "late-migrant" dummy, for instance, is now significant and positive for younger individuals, confirming the findings of Faggian et al. (2007a, b) for the UK.

Individual characteristics (**IND**) include:

Gender: A dummy variable for female respondents is included, since most labor economics studies have shown that women suffer from a salary penalty in the labor market. Similar results have been found also for female graduates specifically (Jewell and Faggian, 2014; Abreu et al., 2015).

Experience: Following the human capital theory (Becker, 1962) individuals with more experience should have higher salaries. As commonly done in labor economics, experience is entered both linearly and squared to control for possible diminishing returns. Experience is defined as the year of the study (2010) minus the year the highest degree was awarded. This is a proxy and assumes that graduates entered the labor market upon graduation, as information on the year the first job started was not provided in the survey.

Race: Two dummy variables for Black and Asian were included to test for possible racial discrimination (Marshall, 1974; Pendakur and Pendakur, 1998).

Disability: A dummy variable included for graduates with disabilities.

Marital status: We included a dummy variable for individuals being married. Studies have shown that married people are paid higher in the labor market (e.g., Chun and Lee, 2001).

Cognitive abilities: As we did not have a direct way to measure innate abilities of students (such as a standardized score), we proxied their cognitive abilities by looking at the quality of the school they attended. Other studies have provided justification for this approach (Faggian and Franklin, 2014). Quality was proxied by a dummy variable for the top 25 higher education institutions in the country.

Governmental support: We also introduced a dummy variable for individuals who benefited from governmental funding either through scholarships or other types of grants. This is an alternative measure of assessing their abilities as normally these awards require exceptional academic achievements.

Education-related (**EDU**) variables include:

Subject studied: Salaries are obviously different for graduates in different fields. For example, Comunian et al. (2010) and Abreu et al. (2012) showed that graduates of more artistic degrees have on average, lower salaries than other graduates. Although our data focus on STEM graduates, there might still be differences across subjects within STEM. NSF classifies the degrees into seven categories: Computer Science and Mathematics, Biological, Agricultural, and Environmental Sciences, Physical and related studies, Social Sciences, Engineers, other Science and Engineering related fields and other non-Science and Engineering related fields. We created a dummy variable for each category and used Social Science as a reference group.

Starting age for BA: To control for more mature students, we also include their age when they started their undergraduate degree.

Highest degree: As our sample included both undergraduate and graduate students, we include dummy variables for their highest degree: bachelor's (reference group), master's degree, PhD and professional degree. Following the human capital theory (Becker, 1962), we would expect graduates with the highest degree to earn more.

Job-related (**JOB**) characteristics include:

Employer sector: We had information on whether graduates entered the private sector, government or academia, so we created dummy variable to control for them (with government as reference group). The expectation is for the private sector to pay the highest salaries (Postel-Vinay and Turon, 2007; Melly, 2005).

Employer size: We included dummies for different employer class-sizes (below 25, 25-100, 101-500 and above 500). Although small and medium enterprises (SMEs) have often been quoted as being more innovative, there is a general sense that larger employers pay, on average, higher salaries (Brown and Medoff,, 1989; Groshen, 1991; Morissette, 1993).

Job 'mobility': We included four dummy variables to check for the effect of changing jobs. Changing jobs or sector might result in a temporary reduction of salary due to a learning and re-training process (Abreu et al. 2014). 'Switchers' are individuals who changed both employer and occupation, 'same job' are individuals who changed employer but not occupation, 'same employer' are individuals who changed occupation but with the same employer. The base category is individuals which did not change either.

Prestigious occupations: Finally, we controlled for occupations which are normally linked to a certain social 'status', such as doctors, lawyers, astrophysicists etc.[4] We followed this approach, because research has shown that people, upon deciding which major to choose for college, they take into consideration expected earnings and certain occupations in society earn more on average (Arcidiacono et. al., 2012, Berger, 1988, Montmarquette et al., 2002).

Job field: The NSF survey includes a series of dummy variables for certain fields of work such as: computers and applications, development and design, management and sales, applied research, and teaching. We include a series of dummy variables for each of this fields.

In the first stage, probit models for the different migration categories are estimated as a function of individual, education and location characteristics. While most of the variables included overlap with the variables describe above, some additional variables are also included. These variables, which are believed to influence the migratory behavior of individuals without directly affecting their final salary, allow us to identify the model. These are:

Parental education: Parental education not only affects the chances of an individual entering college, it might also affect the location of that college. First, individuals coming from a household of highly educated individuals are more likely to have the financial means to migrate to study if they so wish. Second, parents might try to send their children to the same institution they attended.

Children: the number of children is also strongly related to chances of migrating. It might also affect salary but only through the effect on the hours worked (and we are restricting our analysis to full-time workers) and the occupation chosen (which we controlled for directly)

Pull-factors at college location: we also controlled for a series of characteristics of the college locations which might increase the chances of students migrating there. These include factors such as heating and cooling hours, expenditures on natural resources,

[4] A complete list of them is provided in Appendix (Table 3).

crime, expenditures on education. A description of the variables included and their source can be found in Appendix (Table 5).

5. RESULTS

5.1 SUMMARY STATISTICS

Before presenting the results of our two-stage multi-treatment correction model, Table 1 presents some basic descriptive statistics of our sample.

Starting with the migration behavior of graduates, the most common category is repeat migrants (34%) followed by late migrants (30%) and non-migrants (21%). Return migrants are only 5% of the sample. Females are 35% of the sample, which is comparable with other studies on STEM subjects (Cech et al., 2013). The mean salary is about $ 77,420, which is higher than the average U.S. GDP per capita ($48,377).[5] This was expected, as we are selecting individuals with very high levels of human capital.

As far as the field of study is concerned, 29% of the individuals was in social sciences, 24% in Biology/Agriculture/Environment, 16% in Physical and related sciences, 15% in Engineering, about 7% in Mathematics and Computer Science, about 6% in subjects related to science and engineering and only 2% in subjects not-related to science and engineering. Interestingly, the majority of graduates in our sample (72%), works for large employers with 500 or more employees.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Ln(salary)	11.34	0.69	Bachelor	0.11	0.31
REPEAT	0.34	0.47	Master	0.08	0.27
RETURN	0.05	0.22	PhD	0.80	0.40
LATEMIG	0.30	0.46	Professional	0.01	0.09
NONMIG	0.21	0.41	Work in academia	0.43	0.49
UNISTAY	0.10	0.31	Work in government	0.11	0.32
Female	0.35	0.48	Work in industry	0.46	0.50

[5] Data from the World Bank in current prices.

Experience	16.59	10.89	Employer size < 25	0.13	0.33
Asian	0.05	0.22	Employer size 25-100	0.05	0.23
Afro-American	0.06	0.23	Employer size 100-500	0.10	0.30
Top25	0.09	0.29	Employer size 500+	0.72	0.45
Math/Computer	0.07	0.25	Field changer	0.56	0.50
Biology/Agriculture	0.24	0.43	Prestigious occupation	0.24	0.42
Physical and related sciences	0.16	0.37	Spouse works	0.74	0.44
Social sciences	0.29	0.45	Work activity: computers and applications	0.07	0.25
Engineering	0.15	0.35	Work activity: development and design	0.17	0.38
S and E related studies	0.06	0.24	Work activity: management and sales	0.48	0.50
Non S and E related studies	0.02	0.15	Work activity: applied research	0.44	0.50
Age start BA	19.03	3.22	Work activity: teaching	0.30	0.46

5.2. Main results

Results of our multi-treatment model (MNMT) are reported in Table 2 for both the whole sample (Model 1) and doctorate holders only (Model 2). Although we present the results for both the OLS and the MNMT, we will be focusing on the MNMT results as the exogeneity test (also reported in Table 2) shows that migration is endogenous and a selection correction is needed. The selectivity-corrected salary differentials indicate that late movers earn around 17.3% less than non-migrants. Restricting to Ph.D. holders does not change the results on late migrants by much (still a penalty although a bit lower, 1.5%). However, now both repeat migration and return migration are more favorable than non-migrating at all (7.1 and 7.6% respectively). While the coefficients on repeat migrants for doctorate holders conform with the findings by previous contributions, such as Jewell and Faggian (2014) for the UK, the result on late migrants is somewhat surprising. Late migration has been found to be the second most “rewarding” migration strategy after repeat migration in the UK, which is contrary to our results for the USA. To check whether this was a context-specific problem or a selectivity issue we compared the results on Table 2 with standard OLS model not corrected for selectivity. While most of the results are the same for the selectivity-corrected and the uncorrected model, the coefficient on late migration is not significant anymore. This, together with the positive and significant coefficient of the late-migration selection term (λ late-migrant), points to a positive hierarchical sorting à la Borjas (1987). In other words, the higher salary for late migrants is not due to late migration itself but to the self-sorting of the “best” individuals into the late migrant group. The opposite seems to apply for Ph.D. holders who are either repeat or return migrants. Model 3 shows evidence of negative sorting (negative and significant coefficients on λ for both repeat and return migrants). Although significant in both models, the selectivity-corrected salary differential for Ph.D. holders repeat migrants (around 7.1%) is higher than the uncorrected one (5.1%) meaning that—given their characteristics—migration is particularly beneficial to these individuals.

Table 2: Multinomial treatment model and OLS results

	All sample		Doctorates	
	MNMT	OLS	MNMT	OLS
	(1)	(2)	(3)	(4)
Repeat-migrant	0.019	0.039***	0.071***	0.051***
	(0.027)	(0.014)	(0.022)	(0.017)
Return-migrant	0.035	0.012	0.076**	0.019
	(0.026)	(0.023)	(0.032)	(0.029)
University-stayer	0.002	−0.004	−0.040	0.003
	(0.026)	(0.018)	(0.031)	(0.024)
Late-migrant	−0.173***	−0.001	−0.151***	0.011
	(0.046)	(0.014)	(0.057)	(0.017)
Individual variables				
Female	−0.186***	−0.176***	−0.198***	−0.190***
	(0.012)	(0.011)	(0.014)	(0.013)
Experience	0.043***	0.042***	0.041***	0.042***
	(0.002)	(0.002)	(0.002)	(0.002)
Experience squared	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Asian	0.097***	0.103***	0.081***	0.089***
	(0.021)	(0.021)	(0.026)	(0.025)
Black	0.045**	0.042**	0.068***	0.066***
	(0.019)	(0.020)	(0.025)	(0.024)
Disability	−0.030*	−0.030*	−0.034*	−0.034*
	(0.019)	(0.019)	(0.020)	(0.020)
Married	0.035**	0.036**	0.010	0.015
	(0.016)	(0.016)	(0.020)	(0.020)
Top 25	0.060***	0.067***	0.067***	0.080***
	(0.017)	(0.016)	(0.019)	(0.018)
Government support	0.035***	0.032***	0.041***	0.044***
	(0.010)	(0.010)	(0.012)	(0.011)
BA start age	−0.002	−0.003	−0.010***	−0.010***
	(0.002)	(0.002)	(0.003)	(0.003)

Subject studied (reference: social sciences)				
Computer/math	0.108***	0.121***	0.073***	0.080***
	(0.020)	(0.020)	(0.024)	(0.023)
Biology/agriculture	−0.005	−0.006	−0.024	−0.025
	(0.015)	(0.015)	(0.016)	(0.016)
Physical and related	−0.030*	−0.029*	−0.043**	−0.043**
	(0.016)	(0.016)	(0.018)	(0.018)
Computer/math	0.108***	0.121***	0.073***	0.080***
	(0.020)	(0.020)	(0.024)	(0.023)
Biology/agriculture	−0.005	−0.006	−0.024	−0.025
	(0.015)	(0.015)	(0.016)	(0.016)
Physical and related	−0.030*	−0.029*	−0.043**	−0.043**
	(0.016)	(0.016)	(0.018)	(0.018)
Engineering	0.103***	0.102***	0.057**	0.055*
	(0.024)	(0.023)	(0.027)	(0.026)
S&E related	0.171***	0.168***	0.121***	0.118***
	(0.023)	(0.023)	(0.028)	(0.028)
Non S&E related	0.129***	0.131***	0.004	0.003
	(0.039)	(0.039)	(0.244)	(0.244)
Type of degree (reference: bachelors)				
Master	0.221***	0.219***		
	(0.024)	(0.024)		
Ph.D.	0.475***	0.473***		
	(0.018)	(0.018)		
Professionals	0.512***	0.518***		
	(0.066)	(0.066)		
Job-related variables				
Sector (reference: government)				
Work in academia	-0.181***	-0.178***	-0.154***	-0.151***
	(0.016)	(0.016)	(0.019)	(0.019)
Work in industry	0.132***	0.135***	0.169***	0.169***
	(0.014)	(0.014)	(0.017)	(0.017)
Employer size (reference: less than 25 employees)				
25-100 employees	0.340***	0.344***	0.392***	0.395***
	(0.031)	(0.031)	(0.039)	(0.039)
101-500 employees	0.351***	0.352***	0.375***	0.376***
	(0.027)	(0.027)	(0.033)	(0.033)
501+ employees	0.456***	0.459***	0.497***	0.498***
	(0.023)	(0.023)	(0.027)	(0.027)
Job mobility (reference: no changes)				
Sector movers	-0.194***	-0.193***	-0.183***	-0.186***
	(0.026)	(0.026)	(0.034)	(0.034)
Same employer	0.014	0.016	0.020	0.020
	(0.020)	(0.020)	(0.026)	(0.026)

Same job	0.048***	0.050***	0.016	0.017
	(0.017)	(0.017)	(0.020)	(0.020)
Field changers	-0.018	-0.018	-0.021*	-0.020*
	(0.011)	(0.011)	(0.012)	(0.012)
Prestigious occupation	0.030*	0.033**	0.034*	0.036*
	(0.017)	(0.017)	(0.018)	(0.018)
Spouse work	−0.071***	−0.069***	−0.073***	−0.072***
	(0.011)	(0.012)	(0.013)	(0.013)
Job field (reference: others)				
Computers and applications	0.013	0.013	−0.010	−0.010
	(0.019)	(0.019)	(0.023)	(0.023)
Development and	0.059***	0.059***	0.025	0.025
	(0.015)	(0.014)	(0.018)	(0.018)
Management and sales	0.183***	0.184***	0.192***	0.191***
	(0.013)	(0.013)	(0.015)	(0.015)
Applied research	0.129***	0.129***	0.146***	0.145***
	(0.012)	(0.012)	(0.014)	(0.013)
Teaching	−0.126***	−0.127***	−0.134***	−0.135***
	(0.016)	(0.016)	(0.018)	(0.018)
Constant	10.121***	10.076***	10.740***	10.695***
	(0.055)	(0.056)	(0.080)	(0.075)
Correction terms				
ln σ	−0.618***		−0.602***	
	(0.044)		(0.047)	
λ university-stayer	−0.014		0.033	
	(0.022)		(0.025)	
λ return-migrant	−0.032**		−0.075***	
	(0.014)		(0.016)	
λ repeat-migrant	0.007		−0.051***	
	(0.030)		(0.016)	
λ late-migrant σ	0.208***		0.199***	
	(0.054)		(0.067)	
	0.539		0.548	
	(0.024)		(0.026)	
Obs.	14,542		11,582	
LRT of exogeneity	14.88		14.90	
p value (for exogeneity)	0.005		0.005	
F-stat		180.99		118.95
		0.31		0.24

Notes: Robust standard errors in parentheses The multinomial treatment model developed by Deb and Trivedi (2006) has been implemented with 3500 replications.

*** p < 0.01; ** p < 0.05; * p < 0.10

As for the results on the other control variables, most conform to expectations and previous literature. Every extra year of experience increase annual salaries on average by 4.3% although at a decreasing rate. Female workers suffer a penalty salary of about 18.6% (and 19.8% if we restrict to Ph.D. holders). This is even higher than what found in other studies, although it is common to find higher values in STEM subjects than other subjects (Jewell and Faggian, 2014). The salary penalty for women in STEM has been subject of discussion for quite few years, and several reports have been produced on the topic (e.g., Cech et al. 2013). Surprisingly, ethnic minorities (Asians and Afro-American) are doing better than Caucasian in our sample. This is contrary to what is generally found for the whole population and it might mean that education (especially in more science-oriented topics) is particularly beneficial to these minorities. This result should be granted further investigation in the future because of its possible policy implications.

As for education-related variables, individuals graduating from one of the top 25 higher education institution are doing better in the labor market, with a salary about 6% higher (and up to 6.7% for Ph.D. holders). This is consistent with both the human capital theory (better universities provide for a better education) and the signaling theory à la Spence (1971) which points to the fact that employers take a degree from a more prestigious university as a "signal" for higher individual abilities. Also, consistent with the human capital theory, are the results on the highest degree achieved. Masters, Ph.D.s and Professional all have a salary premium over Bachelors and it is a substantial one (going from 22.1% for Masters to an astounding 51.2% for professionals). As for the subject studied, all subjects do better than social sciences, except physical sciences (negative coefficient but significant at 10. Also in the line of the human capital theory is the higher salary (by about 3.5%) of individuals who benefitted from governmental funds. As stated previously, only the best students are selected for these grants, so they can be seen as another signal for their abilities.

Lastly, the job-related controls show an advantage of working in industry vis-à-vis academia. Russo (2010) finds that salaries in academia are on average 30% less than those in industry in North America. Similarly, we find that working in industry pays about 13.2% more, and working in academia about 18.1% less, than working in the governmental sector. So the difference between academia and industry can be estimated as about 31%, even after controlling for all the other factors included in our model. Prestigious occupations offer an extra “reward” of about 3% although only significant at 10% significance level. As for employer size, it seems that the bigger the better. The salary monotonically increases with the size of the company, with the largest employers (more than 500 employees) giving, on average, an annual salary about 45.6% higher than small companies with less than 25 employees. Different reasons might be behind this result. Small firms are much less likely than large firms to provide their employees and their managers with formal training (Storey, 2004). There might also be some peer and learning effects (Cornelissen et al., 2013). Among the different sectors, teaching is the lowest paid, while management and sales, development and design and applied research are paid the most. Finally, keeping the same type of job is associated with a wage premium, while changing sector gives a salary penalty (at least in the short-run. This is compatible with the idea that some of the human capital accumulated during the working life is “specific”, i.e., it cannot be transferred to other jobs or sectors and hence is not rewarded.

5.3 First-stage results

First-stage results are reported in “Appendix” (Table 4). The first stage of a multi-treatment model (MNMT) is a simple multinomial model with sequential migration categories as dependent variables. As in the second stage, we use as base category non-migrants. The multinomial model performs well with a very high value for the chi-square test of joint significance (2839.40 and a p-value of 0.000).

Although we are not entering in a detailed discussion of the sign and magnitude of the independent variables, most results follow expectations. For example, black Americans are less likely to be repeat, late migrants or university stayers than non-migrants. On the opposite, parental education increases the likelihood of being repeat-migrants (hence having a higher migration propensity) and so does have governmental support or being older. These factors reduce the financial constraints that might hamper a migration movement. Also worth noting is that female graduates are less likely to be repeat or late migrants. While Faggian et al. (2007a, b) found the same result for late migration in the UK, they also found that female graduates were actually more likely to be repeat migrants than their male counterpart. However, their sample was restricted to very young individuals who were interviewed only 6 months after graduations. As such, family commitment and the dual-body problems were not affecting their results nearly as much. Another interesting result is that Ivy League schools are less likely to produce university stayers, i.e., graduates who stay locally after finishing their degree. This result is also in line with the findings for the UK that more prestigious universities cater for the whole country and not just the local labor market. As such, their graduates are the most mobile.

6. Conclusions

Our study represents a first attempt to shed light on the phenomenon of sequential graduate migration in the USA and its relationship with labor market success. While several studies on the topic have been published in Europe, little is known for the USA still.

By using a multi-treatment model to correct for possible selectivity issues, we assess the effect of the two combined migration decisions, i.e. migrating to study and migrating to work, on the annual average salary of degree holders. We found that different migration behaviors are associated with either a salary increase or a salary penalty. Specifically, repeat migrants have a salary premium of about 6% while late migrants a salary penalty of over 16%. This holds after controlling for possible hierarchical sorting *à la* Borjas (1987). In fact, we find that selectivity or sorting does matter. The correction factors in the multi-treatment model are significant for all the migration categories, although the strongest for repeat and late migrants. In particular, we found that late migrants suffer from positive hierarchical sorting, while repeat migrants suffer from negative hierarchical sorting. As such, repeat migrants are doing better, and late migrants much worse, than what expected without a control for selectivity.

Despite being just an initial analysis, the current contribution opens up the way for a series of future extensions with important policy implications. Firstly, the issue of gender differences should be addressed more specifically. It would be interesting to see if gender-specific multi-treatment models give different results on the significant parameters and whether the optimal migration strategies are different between the two genders. The same can be said with regard to ethnicity. One of the most counter-intuitive results of our analysis is that ethnic minorities do better than other ethnic groups once selectivity is corrected for. This is contrary to what previously found in the literature for the general population (i.e., not just highly educated individuals) and without selectivity-correction. If highly-educated individuals belonging to ethnic minorities manage to more than compensate for possible discriminatory factors, this would be good news for the proponents of education as a means for upper social mobility.

All in all, the link between migration and career paths of highly educated individuals is of paramount importance not only for individuals but also for regional economic performance and more studies are needed on the topic in North America.

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Appendix

Table 3: List of prestigious occupations

Aerospace, aeronautical and astronautical engineering	Law
Architectural Engineering	Materials engineering
Architecture and environmental design	Mechanical engineering
Astronomy and astrophysics	Medicine
Biochemistry/Biophysics	Metallurgical engineering
Biomedical engineering	Mining and minerals engineering
Business administration and management	Molecular Biology
Chemical engineering	Naval architecture and marine engineering
Civil Engineering	Nuclear engineering
Computer and systems engineering	Operations research
Computer and information sciences	Petroleum Engineering
Electrical, electronics and communications engineering	Pharmacy
Engineering, general	Public health
Geophysical and geological engineering	Statistics

NOTES: The variable NDGRMED has been used for the construction of this list.

Table 4: First stage (multinomial logit) results

	Repeat-migrant	Return-migrant	Late-migrant	University stayer
Female	-0.289***	-0.146	-0.518***	-0.019
Governmental support	0.276***	0.014	0.167**	-0.121
Asian	-0.074	0.018	0.002	0.239
Black	-0.249*	0.029	-0.406***	-0.355***
Age	0.038***	0.009*	0.028***	-0.016***
Ivy School	1.086***	1.226***	-0.311	-1.532***
Children	0.07	0.086	-0.094	0.044
Father's education	0.132***	0.053	-0.166***	-0.257***
Mother's education	0.139***	-0.018	-0.041	-0.110***
Mathematics/Computer	-0.360***	-0.108	-0.546***	-0.114
Engineering	-0.116	0.006	-0.004	0.032
Individual income tax	0.105	0.264***	0.337***	0.300***
Education expenditures	-0.132	-0.211**	0.088	-0.251***
Unemployment	0.012	-0.023	0.012	-0.039**
Heating * Cooling hours	0.024	0.026	0.037	0.028
Population (in millions)	0.026***	0.018***	0.046***	0.015***
Average Yearly Income	-0.020**	-0.011	-0.064***	-0.007
Bank Ratio	0.223***	-0.135**	0.051	-0.227***
Community hospital beds	-0.003***	-0.002**	-0.001**	0.000
Property crimes	-0.026	0.260***	-0.043	0.329***
Recreation expenditures	0.042	-0.058**	-0.036	-0.100***
Natural resources	-0.004	0.007	-0.003	0.007
Constant	-2.485***	-2.104***	0.264	2.656***
Observations	14,542			
LR $\chi2$ (80)	2839.40			
Prob > $\chi2$	0.000			

Table 5: Summary of variables used in both first-stage and main equations

Variable name	Variable description	Source
Salary	The logarithm of individual salary	SESTAT
REPEAT	= 1 for all those individual who are born in state A, studied in state B, and work in state C, where A, B, and C are different to each other.	Own calculation
RETURN	= 1 if an individual returns to his state of birth after he finished his studies in a state different from birth state.	Own calculation
LATEMIG	= 1 for individuals who left their state to find employment in another state.	Own calculation
NONMIG	= 1 for individuals who never moved from their state of birth, either for education purposes or for job.	Own calculation
UNISTAY	= 1 for individuals who had their education in a state different from the state of birth, and who continue to work in that state.	Own calculation
Gender	= 1 if the person is female.	SESTAT
Age	Individual's age.	SESTAT
Experience	A proxy for experience that equals the difference of the survey year to the year an individual obtained his/her degree.	Own calculation
Asian	= 1 if the individual is Asian	SESTAT
Black	= 1 if the individual is Black	SESTAT
Disability	= 1 if the individual reported any kind of disability	SESTAT
Marital status	= 1 if individual is married	SESTAT
Top25	= 1 for those studied in the top 25 U.S. institutions in ARWU list	Own calculation
Ivy School	Dummy variable for individuals who have graduated from IVY schools. This variable was constructed given the institutions code provided by SESTAT.	Own calculation
Government support	= 1 if an individual's work during this or the previous calendar year was supported by the U.S. government.	SESTAT
Math/Computer	= 1 if this major is selected	SESTAT
Biology/Agriculture	= 1 if this major is selected	SESTAT
Physical and related sciences	= 1 if this major is selected	SESTAT
Engineering	= 1 if this major is selected	SESTAT
S and E related studies	= 1 if this major is selected	SESTAT
Non S and E related studies	= 1 if this major is selected	SESTAT
Starting age for BA	A proxy for an individual's starting age of the bachelor degree. Age – (Survey Year – Year got BA) – 4 There is the rough assumption that individuals finish their studies in four years.	Own calculation
Master	= 1 for individuals who hold a Master	SESTAT
PhD	= 1 for individual who hold a PhD	SESTAT
Professionals	= 1 for individuals who graduates in majors such as Medical Sciences and Law.	SESTAT
Employment in academia	= 1 for individuals who work in academia	SESTAT
Employment in the private sector	= 1 for individuals who work in industry	SESTAT
Employer size: 25-100	= 1 if employer employs 25 to 100 individuals	Own calculation
Employer size: 100-500	= 1 if employer employs 101 to 500 individuals	Own calculation

Employer size: 500+	= 1 if employer employs more than 500 individuals	Own calculation
Sector movers	= 1 for individuals who have changed their sector of work	Own calculation
Same employer	= 1 for individuals who work with the same employer	Own calculation
Same job	= 1 for the individuals who perform the same job	Own calculation
Field changers	Dummy that takes value 1 for those with more than BA degree, whose second degree is of different major.	Own calculation
Prestigious occupation	This is a dummy variable that takes value 1 for occupations that are [historically] valued in society as being "prestigious", such as lawyers, doctors, civil/electric engineers, architects, astronautical engineering, molecular biology etc. More information is found in Appendix A.	Own calculation
Father's education	This variable indicates father's educational level. SESTAT provides the following values: [1] Less than high school completed, [2] High school diploma or equivalent, [3] some college, vocational, or trade school, [4] Bachelor's degree, [5] Master's degree, [6] Professional degree, and [7] Doctorate.	SESTAT
Mother's education	This variable indicates mother's educational level. SESTAT provides the following values: [1] Less than high school completed, [2] High school diploma or equivalent, [3] some college, vocational, or trade school, [4] Bachelor's degree, [5] Master's degree, [6] Professional degree, and [7] Doctorate.	SESTAT
Spouse work	= 1 for individuals whose spouse works.	SESTAT
Children	= 1 for individuals who have children	SESTAT
Work activity: computers and applications	= 1 if the work activity is as left column cell indicates.	SESTAT
Work activity: development and design	[same as above]	SESTAT
Work activity: management and sales	[same as above]	SESTAT
Work activity: applied research	[same as above]	SESTAT
Work activity: teaching	[same as above]	SESTAT
Average individual income tax	This variable indicates the difference of the average individual income tax between the state of birth and employment state.	BLS
Average education expenditures	This variable indicates the difference of the average educational expenditure between the state of birth and employment state.	BLS
Unemployment	This variable indicates the difference of the unemployment rate between the state of birth and employment state.	BLS
Heating days	This variable is the difference of the average heating days reported between the state of birth and employment state.	NOAA
Cooling days	This variable is the difference of the average cooling days reported between the state of birth and employment state.	NOAA

Population	The difference of the number of individuals living in a state between the state of birth and employment state.	CPS
Average annual income	The difference of the average annual income between the state of birth and employment state.	CPS
Bank ratio	This variable indicates the number of banks per 10,000 individuals. Information about the number of bank establishments have been obtained from CCD2000. It is the difference of the value reported for the state of birth and employment state.	Own calculation
Community hospital beds	The number of community hospital beds per 10,000 individuals. It is the difference of the value reported for the state of birth and employment state.	CCD2007
Property crimes	This variable indicates all known property crimes that have occurred in a state (table A.6 of CCD2007). Includes burglary, larceny-theft, and motor vehicle theft. It is the difference of the value reported for the state of birth and employment state.	CCD2007
Recreation expenditures	This is the per capita amount of recreation expenditures. The monetary value is thousands of dollars. It is the difference of the value reported for the state of birth and employment state.	U.S. Census Bureau
Natural resources expenditures	This is the per capita amount of natural resources expenditures. The monetary value is thousands of dollars. It is the difference of the value reported for the state of birth and employment state.	U.S. Census Bureau

NOTES: NOAA stands for U.S. National Oceanic and Atmospheric Administration; CCD2007 stands for City and County Databook of 2007

Table 6: Results on the restricted sample of individuals aged 25–40

	Repeat-migrant	Return-migrant	Late-migrant	University-stayer
(a) First-stage results (multinomial logit)				
Female	-0.060	0.178	-0.325***	-0.118
Governmental support	0.382***	0.225	0.279***	0.209*
Asian	-0.294*	-0.455*	-0.276	-0.231
Black	0.367**	0.413*	0.308*	0.368*
Age	0.170***	0.029	0.138***	0.042***
Ivy school	2.734***	3.037***	1.257***	1.324***
Children	-0.519***	-0.048	-0.597***	-0.052
Father's education	0.348***	0.259***	0.059	0.255***
Mother's education	0.197***	-0.025	0.071*	0.038
Mathematics/Computer Science	-0.399**	0.267	-0.604***	0.255
Engineering	0.177	0.424**	0.122	-0.027
Individual income tax	-0.249**	0.021	-0.048	-0.296*
Education expenditures	0.080	-0.058	0.320**	0.266*
Unemployment	0.019	0.014*	0.060**	0.028
Heating* cooling hours	-0.012	0.013	0.052	-0.068
Population (in millions)	0.008	0.001	0.029***	-0.012
Average yearly income	-0.040***	-0.003	-0.082***	0.009
Bank ratio	0.269***	-0.019	0.170**	0.216**
Community hospital beds	-0.002***	0.000	-0.001	0.000
Property crimes	-0.273***	0.025	-0.343***	-0.243
Recreation expenditures	0.124***	0.013	0.013	0.095*
Natural resources expenditures	-0.012*	0.003	-0.001	-0.011
Constant	-8.498***	-4.247***	-5.388***	-3.519***
Observations		4927		
Wald χ^2 (127)		3844.57		
LR- pseudolikelihood		-10367.513		
Prob > χ^2		0.000		
	All sample		Doctorates	
	MNMT	OLS	MNMT	OLS
	(1)	(2)	(3)	(4)
(b) Second-stage results (MNMT)				
Repeat-migrant	0.095***	0.026	0.129***	0.067***
	(0.025)	(0.021)	(0.030)	(0.029)
Return-migrant	-0.062	0.011	0.055	0.075*
	(0.044)	(0.030)	(0.042)	(0.043)
University-stayer	-0.036	-0.010	0.035	0.024
	(0.025)	(0.023)	(0.042)	(0.042)
Late-migrant	0.050**	-0.017	-0.041	0.024
	(0.021)	(0.020)	(0.030)	(0.030)
Individual variables				
Female	-0.121***	-0.125***	-0.139***	-0.135***
	(0.015)	(0.015)	(0.022)	-0.135***
Experience	0.049***	0.049***	0.049***	0.050***
	(0.010)	(0.010)	(0.017)	(0.017)
Experience squared	-0.001	-0.001	-0.001	-0.001

	(0.001)	(0.001)	(0.001)	(0.001)
Asian	0.102***	0.100***	0.071***	0.077***
	(0.026)	(0.026)	(0.037)	(0.037)
Black	0.002	-0.010	0.008	0.008
	(0.029)	(0.310)	(0.051)	(0.051)
Disability	0.017	0.021	0.087	0.084
	(0.038)	(0.037)	(0.057)	(0.057)
Married	0.028	0.023	-0.018	-0.011
	(0.021)	(0.021)	(0.030)	(0.030)
Top 25	0.090***	0.094***	0.119***	0.129***
	0.129***	(0.021)	(0.027)	(0.027)
Government support	-0.045***	-0.044***	-0.034	-0.029
	(0.016)	(0.016)	(0.022)	(0.022)
BA start age	-0.004	-0.002	-0.021***	-0.021***
	(0.004)	(0.004)	(0.007)	(0.007)
Subject studied (reference: Social Sciences)				
Computer/Math	0.156***	0.147***	0.061	0.066
	(0.031)	(0.031)	(0.049)	(0.049)
Biology/Agriculture	-0.003	-0.012	-0.044	-0.046
	(0.023)	(0.024)	(0.030)	(0.030)
Physical and related	-0.013	-0.019	-0.050	-0.054*
	(0.024)	(0.024)	(0.031)	(0.031)
Engineering	0.200***	0.196***	0.110**	0.110**
	(0.035)	(0.035)	(0.052)	(0.052)
S&E related	0.202***	0.199***	0.201***	0.193***
	(0.036)	(0.036)	(0.054)	(0.054)
Non S&E related	0.240***	0.236***	—	—
	(0.041)	(0.041)		
Type of degree (reference: bachelors)				
Master	0.205***	0.215***		
	(0.027)	(0.027)		
Ph.D.	0.563***	0.582***		
	(0.023)	(0.023)		
Professionals	0.501***	0.513***		
	(0.062)	(0.062)		
Job-related variables				
Sector (reference: government)				
Work in academia	-0.302***	-0.305***	-0.287***	-0.288***
	(0.026)	(0.026)	(0.034)	(0.034)
Work in industry	0.065***	0.065***	0.096***	0.097***
	(0.019)	(0.019)	(0.030)	(0.030)
Employer size (reference: less than 25 employees)				
25-100 employees	0.238***	0.242***	0.446***	0.452***
	(0.043)	(0.043)	(0.086)	(0.086)
101-500 employees	0.266***	0.266***	0.349***	0.356***
	(0.039)	(0.039)	(0.076)	(0.076)
501+ employees	0.314***	0.314***	0.401***	0.407***
	(0.035)	(0.035)	(0.067)	(0.068)
Job mobility (reference: no changes)				
Sector movers	-0.147**	-0.146***	-0.041	-0.048
	(0.032)	(0.033)	(0.049)	(0.050)
Same employer	-0.003	0.000	0.022	0.023
	(0.026)	(0.026)	(0.049)	(0.049)
Same job	0.083***	0.086***	0.023	0.022
	(0.022)	(0.023)	(0.035)	(0.035)

Field changers	-0.029	-0.026	-0.057***	-0.055***
	(0.019)	(0.019)	(0.024)	(0.024)
Prestigious occupation	-0.016	-0.015	-0.038	-0.036
	(0.024)	(0.024)	(0.031)	(0.031)
Spouse work	-0.090***	-0.083***	-0.097***	-0.096***
	(0.018)	(0.019)	(0.027)	(0.027)
Job field (reference: others)				
Computers and applications	0.058**	0.054**	-0.003	-0.007
	(0.026)	(0.026)	(0.045)	(0.045)
Development and design	0.091***	0.090***	0.014	0.008
	(0.019)	(0.019)	(0.032)	(0.032)
Management and sales	0.117***	0.120***	0.094***	0.096***
	(0.019)	(0.019)	(0.027)	(0.027)
Applied research	0.041***	0.043***	0.052**	0.051*
	(0.019)	(0.019)	(0.026)	(0.026)
Teaching	-0.093***	-0.096***	-0.097***	-0.098***
	(0.025)	(0.026)	(0.032)	(0.032)
Constant	10.249***	10.219***	11.151***	11.136***
	(0.100)	(0.103)	(0.169)	(0.169)
Correction terms				
ln σ	-0.731***		-0.725***	
	-0.731***		(0.075)	
λ university-stayer	0.035**		-0.022***	
	(0.015)		(0.006)	
λ return-migrant	0.078**		0.013***	
	(0.033)		(0.003)	
λ repeat-migrant	-0.090***		-0.096***	
	(0.018)		(0.015)	
λ late-migrant	-0.081***		0.088***	
	(0.008)		(0.011)	
σ	0.482		0.484	
	(0.024)		(0.036)	
Obs.	4927	4967	2329	2354
LRT of exogeneity	11.24		78.78	
p-value for exogeneity	0.024		0.000	
F-stat		64.1		34.45
R^2		0.35		0.28

Notes: Robust standard errors in parentheses. The multinomial treatment model developed by Deb and Trivedi (2006) has been implemented with 3500 replications.

*** p < 0.01; ** p < 0.05; * p < 0.10